Macroeconomic Forecasting in Poland: Lessons From the COVID-19 Outbreak.

Rybacki, Jakub and Gniazdowski, Michał

SGH Warsaw School of Economics, Polish Economic Institute

11 May 2021

Jakub Rybacki[1]

Michał Gniazdowski[2]

Macroeconomic Forecasting in Poland: Lessons From the COVID-19 Outbreak.

Abstract

The aim of this paper is to analyze the forecast errors of Polish professional forecasters under the COVID-19 crisis in 2020—based on the Parkiet competition. This analysis shows that after the initial disruption related to imposed lockdown in March and April, commercial economists were capable of lowering their forecasts errors of the industrial production and retail sales. On the other hand, the far worse performance has been seen in the case of the market variable; either the size of errors or the disagreement were elevated throughout the entirety of 2020. Furthermore, long-term forecasts that were produced during the first year of the pandemic have been characterized with visible inconsistencies (i.e., projections of economic growth were similar when forecasters either assumed a strong increase in unemployment or when they did not).

Keywords: GDP forecasting, Labor Market forecasts, COVID-19

JEL classification codes: E27, E32, E37

[1] Polish Economic Institute & Warsaw School of Economics - Collegium of Economic Analysis, e-mail: jr70663@sgh.waw.pl

[2] Polish Economic Institute

1. Introduction

The aim of this paper is to evaluate the forecasts errors of Polish professional forecasters during the year 2020 (i.e., in the wake of the COVID-19 pandemic). Such an analysis should provide guidance for the statistical office. This will help to answer which areas provide reliable public information for the basis of creating forecasts. This study is based on a database of individual forecasts from two competitions that are managed by a daily newspaper named Rzeczpospolita.

First, we analyzed the accuracy of monthly nowcasts, that were based on 12 polls, published from January to December 2020. Nowcast stands for the estimate of the current data release, which was published prior to the official information. Estimates are published by approximately 27 analysts. Second, we analyzed four series of one-year projections that were published by 30 economic experts. Analysts provides information about expected GDP growth, their components, and the unemployment rate. We then analyze that information in the context for either unbiasedness or a rationality of revisions.

The monthly polls show that the COVID-19 outbreak resulted in the increase of both industrial production and retail sales forecasts errors, which caused a large amount of disagreement for the first three months of the pandemic. After that period, commercial economists were capable of reducing errors. On the other hand, economists have a much worse performance in forecasting the conditions of the labor market. Both forecasts errors and the disagreement remained elevated for the entire year.

The one year ahead forecasts, which were produced during the COVID-19 pandemic, were not statistically efficient. First, revisions were often exaggerated in the wake of lockdowns. Second, labor market errors were one-sided. Furthermore, there are evident inconsistencies between the revisions of macroeconomic variables. Revisions of the labor market forecast has not influenced estimates for Gross Domestic Product (GDP) growth, despite the strong scale of changes.

This manuscript is structured as follows. Section 2 provides a literature review on macroeconomic forecasting and irregularities that are visible in Poland. Section 3 provides a description of used dataset. Section 4 delivers information about the methodology of our research. Section 5 summarizes problems related to nowcasting of macroeconomic variables during the COVID-19 outbreak. Section 6 discusses the inconsistencies that are visible in the one year ahead forecasts. Finally, section 7 concludes the paper.

2. Literature Review

The COVID-19 shock has created unprecedented volatility in the macroeconomic time series, which strongly influences forecasting. During the period of the first Great Lockdown (March to May 2020), the average lifetime of macroeconomic forecasts was likely to not survive one month. Second, in the summer of 2020, forecasts prepared worldwide were systematically more pessimistic when compared to the future realizations; real tam economic surprise indices, such as presented in the work of (Scotti, 2016), reached an all-time high.

In a response, the academic literature on macroeconomic forecasting became focused on the correct estimation of traditional models, as well as developments of the nowcasting techniques (Foroni et al., 2020; Lenza & Primiceri, 2020). Researchers usually attempt to build complex solutions to either incorporate a real time flow of information (Mamaysky, 2020) or adapt epidemiological frameworks (Eichenbaum et al., 2020). Although we do not want to depreciate these efforts, one needs to note that those outcomes are usually not publicly available. In addition to that, replication will exceed the capacity of business economists. The commercial work consumes a great majority of time; this involves the publishing of daily comments, as well as the providing of presentations or calls to both internal and external clients. This limits the possibilities for using complex econometrics. Therefore, their practical application may be dead-on-arrival.

The forecasts produced during economic crisis are usually imperfect; the errors are usually biased and the revisions are sometimes irrational (Eicher et al., 2019). The weak performance is present in the case of commercial economists and international institutions, like the International Monetary Fund or European Commission—they often make similar mistakes (An et al., 2018).

Nevertheless, a relatively low number of researches are trying to answer this question: in which areas are forecasting professionals creating the biggest mistakes and how can we improve on said mistakes? This study aims to fill that gap. It presents a detailed analysis of the economic forecasts in Poland; where data availability of short-term macroeconomic projections is far greater than that of the most developed European nation.

This analysis is focused on the behavior of financial business economists. The key thing to understand, is that the goal of a commercial professional is not to minimize Root Means Squared Errors (RMSE) at any cost, but rather to represent their institution. This results in motivational biases - some of them have been presented in the (Rybacki, 2020). This problem has been visible, especially during the COVID-19 pandemic. After the first lockdowns, analysts published numbers which had poor justification; this is because they were expected to present some view e.g., for risk management purposes or public statements in the press.

This problem has been evident in the National Bank of Poland's macroeconomic survey of professional forecasters (Kowalczyk, 2010); economists show very wide bands of uncertainty in 2020, as well as a declining risk in 2021. Such an assessment is mathematically controversial; the GDP growth for 2021 is strictly related to the previous year's performance. Therefore, such a result was unlikely to be produced by the formal macroeconomic model. This evidence highlights the judgmental role in the forecasting during the period of macroeconomic stress. Although such heuristics are both flawed and prone to biases, there is strong evidence that shows that human expertise is beneficial during periods of excessive uncertainty (Lawrence et al., 2006).

We are focusing on the forecasts produced during the pandemic as they have much greater implications, as opposed to mere standard times; they shape the financial market expectations and, consequently, become a basis for policymaking. Particularly, they are used to justify what scale of government interventions, like financial shields, are required. The analysis of forecasts accuracy does not allow for the general reasoning about the normal times; statistical efficiency, in such cases, were presented in the (Rybacki, 2021).

From a perspective of institutions, like the statistical office or the central bank, such an evaluation should help to answer which areas' publicly available information give a more reliable basis in order to create forecasts.

3. Database

This analysis is based on the database of individual forecasts that participated in both the Parkiet forecasting competition for monthly nowcasts, during the years 2015 to 2020, and the Rzeczpospolita competition—during the year 2020.

The Parkiet monthly consensus poll contains information about every major indicator that is published by both the Central Statistical Office (GUS) and the National Bank of Poland on a continuous basis. These include Purchasing Managers Index (PMI), Consumer and Producer Price Index (CPI & PPI), industrial production, retail sales, construction output, corporate employment & wages, unemployment rate, exports, imports, and current account (CA) balance. Macroeconomic forecasts usually describe the Year-on-Year growth. In the case of PMI, the jury decided to use index level; and in the case of foreign trade variables, EUR denominated figures. The CA balance is also presented as a level. In 2020, there were 24 participants; 22 of them (92%) represent banks or financial intermediaries. The other two participants represent think-tanks.

The consensus for the Rzeczpospolita forecasting competition is collected quarterly. In 2020, analysts provided information about the year-on-year growth of GDP, private consumption, gross fixed capital formation, CPI, and the unemployment rate level. There were approximately 30 participants. Again, a similar proportion of participants represent commercial financial institutions.

These two contests are recognized as the most prestigious competitions among the many financial institutions in Poland. The number of participants is higher, when compared to the National Bank of Poland's survey of professional forecasters (SPF). The panel is more balanced; throughout a year, there are practically no cases in which a participant failed to complete a survey. This is not a case of SPF.

Furthermore, the poll is developed with constant contact with commercial economists. Therefore, it is scheduled to be perfectly synchronized with the estimation of nowcasts. This is not always true in the cases of Bloomberg and Reuters consensus. For example, Bloomberg requires a short-term estimate of flash CPI a week before data release. These estimates are made prior to the publication of the GUS statistical bulletin. Therefore, results are frequently different than polls that are later published by Reuters, the Polish Press Agency, and Parkiet.

4. Methodology

This section describes the methodology. The research is divided into two parts. In the first part, we analyze the simple descriptive statistics of forecasts errors for the short-term macroeconomic variables. We attempt to analyze magnitude forecasts uncertainty of four macroeconomic indicators, which were the strongest affected by the pandemic (i.e., corporate employment, wages, industrial production, and retail sales).

Our analysis is based on the dispersion between the forecasts. We calculate an interquartile range (IQR) of individual estimates in the subsequent months of 2020. This statistic eliminates 25% of the most pessimistic and the most optimistic forecasts. We compare these values to the average levels from the years 2015 to 2019, separately, for each subsequent month. We also wish to verify whether analysts were capable of lowering their errors after the initial lockdowns in March to April 2020. We propose a simple equation:

$$\frac{IQR_t}{IQR_{avg,m}} = a_0 + a_1 * t + e_t \quad (1)$$

Where IQR_t is an interquartile range for the forecast at the time, t, $IQR_{avg,m}$ is an average interquartile range for forecasts in the years 2015 to 2019 for the month m, a_0 and a_1 are estimated parameters, e_t is a random disturbance. We expect a_1 to be:

1. Negative for activity forecasts; i.e., the industrial production and the retail sales.
2. Positive or statistically insignificant for the employment figures.

We expect to see lowering disagreement in case of industrial production, retail sales, and corporate wages. Corporate employment is likely to have elevated disagreement.

In the second part, we attempt to analyze the efficiency of the forecasts and the consistency between revisions of long-term estimates based on panel models. This analysis is also based on the database of individual forecasts, which participate in the second competition (the Rzeczpospolita contest) for the best macroeconomic analysts. We are analyzing forecasts for the two macroeconomic indicators: GDP growth and the unemployment rate.

First, we attempt to answer whether forecasts were efficiently in line with the Nordhaus definition (Nordhaus, 1987). This concept assumes that revisions should be totally unpredictable (i.e., information about previous forecasts should not give any clues on how they will be changed in the next months). The systemic errors were present in the Polish GDP forecasts—even before the pandemic (Rybacki, 2021). We propose a simple model:

$$d(forecast_t) = a_0 + a_1 * d(forecast_{t-1}) + e_t \quad (2)$$

The notation is similar when compared to equation 1. We expect parameter a_0 to be different than zero. In such a case, published estimates have obvious one-sided biases. We also see whether parameter a_1 is negative and less than one. This implies that analysts are making excessive corrections, which are reverted in the next round of forecasts.

Second, we would like to verify whether forecasts revisions were rational. The increase of the unemployment rate should have a negative effect on the growth forecasts and consumption. We attempt to estimate a simple model where the revision of consumption forecast ($fConsumption_t$) is explained by the revision of unemployment rate ($fLabor_{t,}$). This formula is presented in equation 4.

$$d(fConsumption_t) = a_0 + \ a_1 * d(fLabor_{t,}) + e_t \tag{3}$$

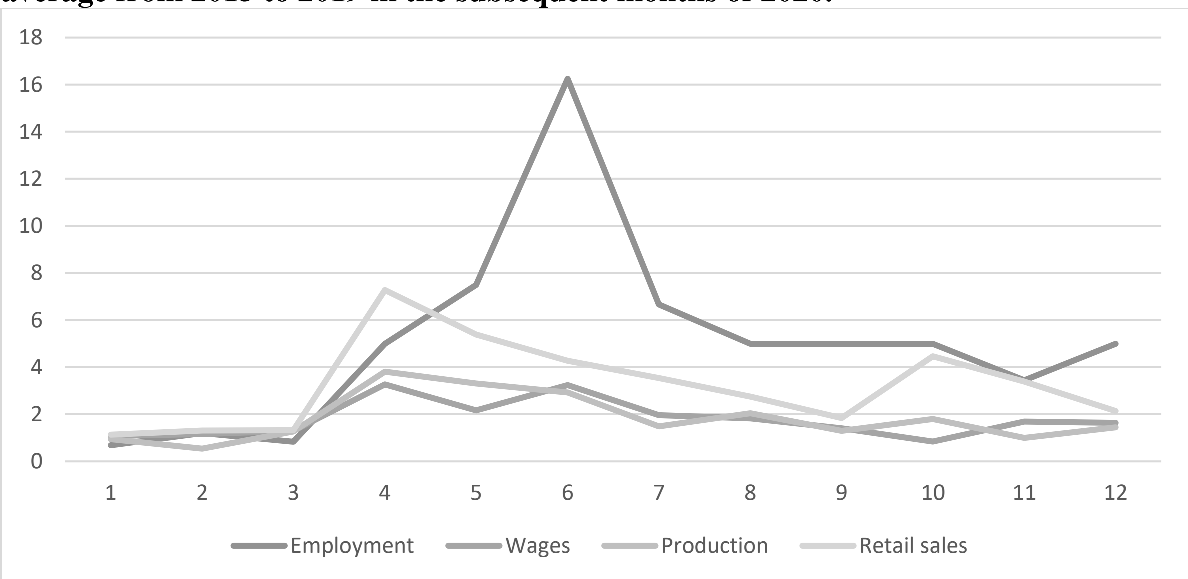
We estimate the independent equations for each period and forecasts horizon. Our aim is to verify whether relationship between these revisions is negative for each time period. Then, we would like to check if the response is different in case of negative and positive revision. Finally, in case of the longer forecasts, we would like to discuss to what extent revisions are related to exogenous assumptions.

5. Nowcasting of monthly activity and labor market conditions after the COVID-19 outbreak.

This section summarizes the accuracy of a nowcasts that was published during 2020. Nowcasts are approximations of current economic conditions that are published prior to the official statistical office data release. The disagreement between the forecasters, consensus errors, and parameters of estimated models are all presented in Tables 1 to 4.

The biggest errors were recorded in April; the data published at that time describes the economic reality from March. Similarly, the scale of uncertainty in this month was also the highest during the entirety of 2020. The interquartile ranges of forecasts are presented in Figure 1. Analysts were forced to forecast effects of the lockdown—an unprecedented event. Given no evidence of such episodes in the past, these actions were blindly accepted.

Fig 1. How many times interquartile range of forecasts was higher comparing to the average from 2015 to 2019 in the subsequent months of 2020.



Source: Rzeczpospolita daily

Analysts improved their accuracy regarding the forecasting of retail sales; errors and disagreement have decreased over time, most likely due to analyzing real time data from both debit and credit card payments[3]. This evidence is confirmed by the model; the a_1 parameter is statistically significant and is equal to -0.46. However, at the end of 2020, the disagreement between the forecasters was still twice higher than before the pandemic and amounted to two to three percentage points. Uncertainty was especially elevated during periods with a greater number of infections. For example, in September, the disagreement was over four times higher than in the years of 2015 to 2019.

Economic experts also had no major problems when it came to forecasting industrial production. During the years of 2015 to 2019, the interquartile range averaged slightly over one percentage point. We also observed similar values in the fourth quarter of 2020. The model confirms fading uncertainty; the estimated parameter a_1 for this variable is equal to -0.31.

From the third quarter onwards, wage forecasts didn't deviate from the usual trend—either. At the end of the year, the disagreement between the forecasters was an approximate 0.3 percentage point. The large fluctuations were only observed in the period of March to May. This resulted from the unclear impact of the anti-crisis government response. The effects of subsidizing compensations were difficult to assess by the commercial analysts. In case of this variable estimated parameter a_1 is equal to -0.22.

Economists cannot effectively forecast employment in the enterprise sector. Normally, analysts make errors of a 0.1 percentage point. They are also nearly unanimous in their forecasts. During the pandemic, these figures were multiple times higher; in June, the disagreement of forecasters was 16 times greater than what has been observed in previous years. At the end of the year, it was 5 times higher than in the years 2015 to 2019, despite even the large fluctuations of the headline figure having vanished.

This evidence is also present in the model. Although the estimated parameter a_1 is negative (-0.61), it is strongly influenced by the June reading. Therefore, the standard deviation of this parameter is high and, contrary to the previous estimations, it is statistically insignificant. This evidence confirms the problem described in the previous paragraph.

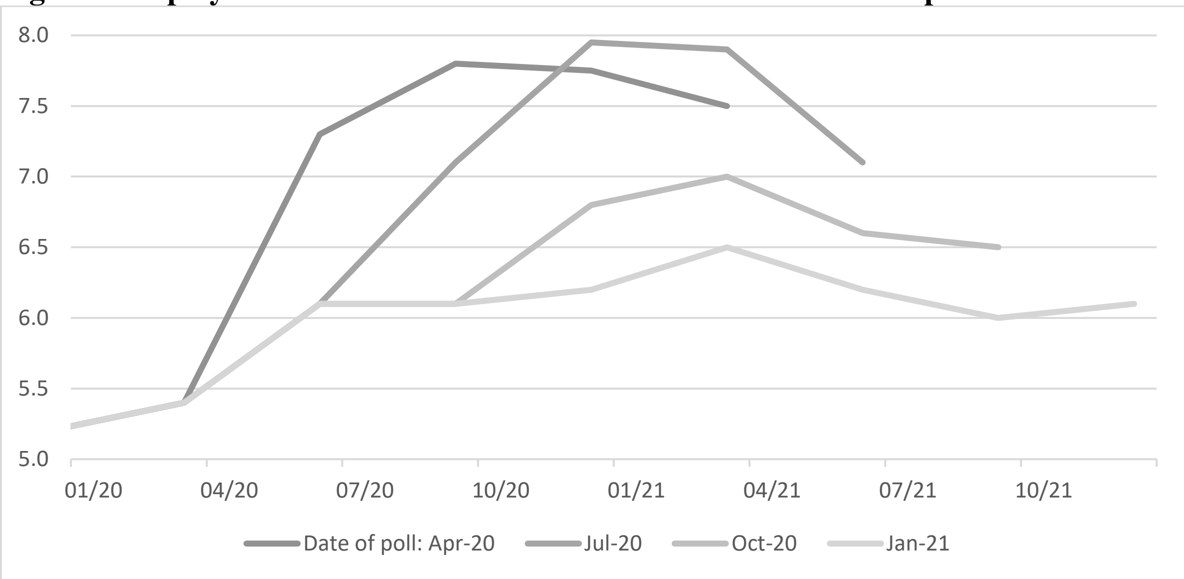
[3] An example of such analysis, is the Santander report regarding consumption expenditure during the restrictions in November 2020, after the country was divided in the yellow and red COVID-19 zones.

6. Macroeconomic forecasting during the COVID-19 pandemic.

This section summarizes the accuracy of long-term forecasts published during 2020, with a horizon of one to three quarters ahead. The model, which is based on equation 2, confirms a lack of efficiency in the case of GDP and in the unemployment rate forecasts. Results are presented in Tables 5 and 6.

A first glance at the consensus reveals that economists systematically presented an overly pessimistic picture of the unemployment rate. The evolution of the consensus duration is presented in Figure 2; the revisions are rather one-sided, so we can see a constant delaying of periods when unemployment was expected to increase.

Fig 2. Unemployment rate consensus forecast under the COVID-19 pandemic

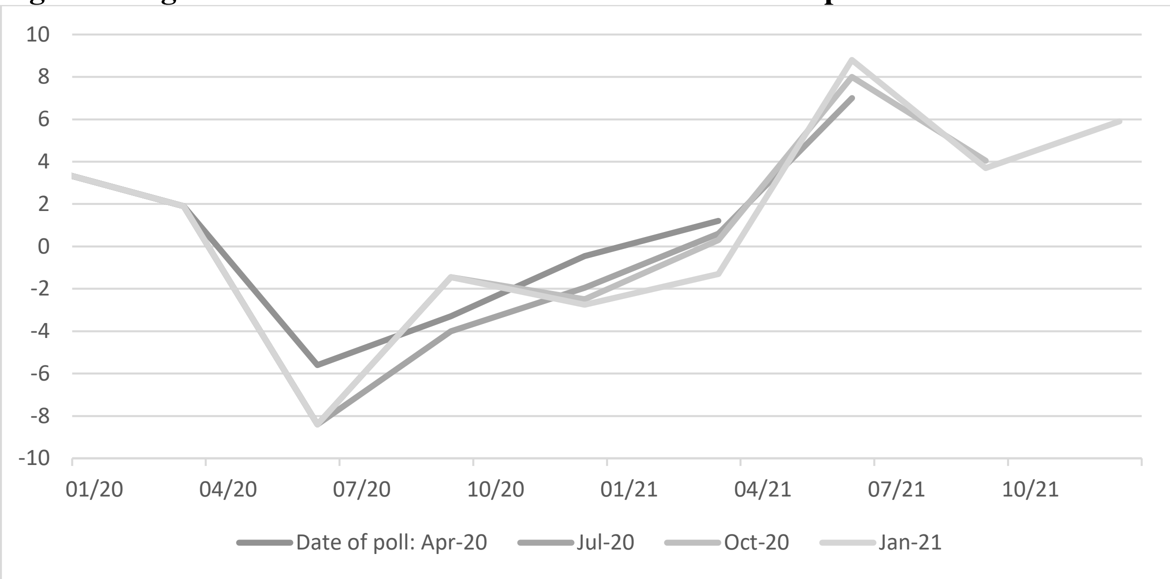


Source: Rzeczpospolita daily

Forecasts were systematically reduced across all horizons (i.e., from the incoming quarter to one year ahead). The biggest reductions were visible in the case of estimates with the lower horizon; within a quarter to publication, analysts lowered estimates – on average – by 0.6pp. The magnitude for other horizons were slightly lower and amounted to 0.3-0.4pp. The negative parameter a_1 suggests a tendency for excess revision; this is especially visible in the case of forecasts from Q2, in which analysts were predicting an imminent contraction of employment.

Analysts have also exaggerated the effects of the economic lockdowns in the case of the GDP forecasts, although the errors of these estimates are less one-sided. After restrictions were lifted in June 2020, Economists started predicting the recovery. They were surprised in the 4Q by the second wave of infections that resulted in another period of excessive negative errors. This evolution of consensus is presented in Figure 3.

Fig 3. GDP growth consensus forecast under the COVID-19 pandemic



Source: Rzeczpospolita daily

The model parameters have similar interpretations like in the case of the unemployment rate. Systematic biases and excessive revisions were present in the economic debate in Poland –even prior to the COVID-19 pandemic (Rybacki, 2021). The period of the pandemic is not different.

The analysis shows a lack of consistency between the revisions of consumption and the unemployment rate. Basic specifications (Table 7) show a positive correlation between amendments to the forecasts for these two variables. When analysts forecasted a better outlook for consumption, they could simultaneously be more pessimistic on the labor market conditions –and vice versa. The relationship is statistically insignificant; still, it is worth considering why revisions of economic activity were detached from the labor market conditions.

We repeated the estimation separately for each period. The direction of revisions was intuitive in the first half of 2020; expectations of bigger unemployment resulted in a worse activity outlook. Nevertheless, the explanatory power of these equations is very weak; the r-squared coefficient is usually lower than 10%. During the second half of 2020, the relationship was broken and changes to labor market assumption were insignificant. The average magnitude of revision – in the consumption corresponding to changes in the labor market assumption – is much lower than in the case of the intercept, which captures exogenous factors like expectations of lockdown conditions. In the case of the longest horizon (three quarters ahead), the impact is three to six times lower. This is presented in Table 8.

7. Policy Conclusions

The COVID-19 pandemic revealed a weak understanding of the labor market conditions among the Polish economists. Problems related to forecasting were visible the in case of identifying current conditions, as well as preparing long term predictions.

If a single analyst is wrong, it is a problem of his or her negligence. However, when a community of analysts is overall incapable of presenting a reliable view on the labor market condition, it is a problem of both fiscal and monetary authorities; their decisions may be based on a very inaccurate picture of the economy. There are three areas in which this should be investigated.

First, the data dissemination policies of the statistical office need to be reviewed. The likely reason behind the problem with both forecasting employment and unemployment, is the lack of sufficient information about the process that is provided by the statistical office.

Second, the public statistics in Poland likely do not have all the necessary information to describe the labor market. The statistical office (GUS) is mainly asking companies about permanent labor contracts. However, the possibilities of employment in Poland are not limited to this form; there is a significant share of both business-to-business and civil law contracts. Broadening the mandate of GUS to gather more information may be am advantageous move.

Finally, greater attention should be directed towards the academia sector. The National Science Centre in Poland is providing funding for various scientific research projects that analyze the shape of the labor market. Unfortunately, the pandemic highlighted that this accumulated knowledge is not supportive during economic downturns. The current recruitment process is not considering potential application of research in the grant mechanisms; furthermore, commercial experts are not accessing the potential viability of the projects. A greater emphasis on these practical aspects should be beneficial.

References:

An, Z., Jalles, J. T., & Loungani, P. (2018). How well do economists forecast recessions? *International Finance*, *21*(2), 100–121. https://doi.org/10.1111/infi.12130

Eichenbaum, M., Rebelo, S., & Trabandt, M. (2020). The Macroeconomics of Epidemics. *National Bureau of Economic Research*. https://doi.org/10.3386/w26882

Eicher, T. S., Kuenzel, D. J., Papageorgiou, C., & Christofides, C. (2019). Forecasts in times of crises. *International Journal of Forecasting*.

https://doi.org/10.1016/j.ijforecast.2019.04.001

Foroni, C., Marcellino, M., & Stevanovic, D. (2020). Forecasting the Covid-19 recession and recovery: Lessons from the financial crisis. *International Journal of Forecasting*. https://doi.org/10.1016/j.ijforecast.2020.12.005

Kowalczyk, H. (2010). O eksperckich ocenach niepewności w ankietach makroekonomicznych. *Bank i Kredyt*, *nr 5*, 101–122.

Lawrence, M., Goodwin, P., O'Connor, M., & Önkal, D. (2006). Judgmental forecasting: A review of progress over the last 25 years. *International Journal of Forecasting*, *22*(3), 493–518. https://doi.org/10.1016/j.ijforecast.2006.03.007

Lenza, M., & Primiceri, G. (2020). How to Estimate a VAR after March 2020. *National Bureau of Economic Research*. https://doi.org/10.3386/w27771

Mamaysky, H. (2020). Financial Markets and News about the Coronavirus. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3565597

Nordhaus, W. D. (1987). Forecasting Efficiency: Concepts and Applications. *The Review of Economics and Statistics*, *69*(4). https://doi.org/10.2307/1935962

Rybacki, J. (2020). Macroeconomic forecasting in Poland: The role of forecasting competitions. *Central European Economic Journal*. https://doi.org/10.2478/ceej-2020-0001

Rybacki, J. (2021). Polish GDP forecast errors: a tale of inefficiency. *Bank i Kredyt*, *52*(2), 123–142.

Scotti, C. (2016). Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. *Journal of Monetary Economics*. https://doi.org/10.1016/j.jmoneco.2016.06.002

Table 1: Forecast characteristics - employment in the enterprise sector

Month of publication	Forecasts error		Forecasts disagreement	
	2020	Median 2015-2019	2020	Median 2015-2019
1	0.0	0.1	0.1	0.1
2	1.1	0.8	0.8	0.7
3	0.0	0.1	0.1	0.1
4	0.5	0.1	0.3	0.1
5	1.5	0.0	0.5	0.1
6	0.6	0.1	0.6	0.0
7	0.5	0.1	0.4	0.1
8	0.8	0.1	0.3	0.1
9	0.2	0.1	0.4	0.1
10	0.1	0.0	0.3	0.1
11	0.1	0.1	0.3	0.1
12	0.2	0.1	0.3	0.1
Estimated parameters				
	Parameter	Standard deviation	T - statistics	P-value
a_0	11.39	3.99	2.85	0.02
a_1	-0.61	0.47	-1.28	0.24

This model is based on the equation presented in formula 1.

Table 2: Forecast characteristics - corporate wages in the enterprise sector

Month of publication	Consensus - Forecasts error		Forecasters' disagreement	
	2020	Median 2015-2019	2020	Median 2015-2019
1	0.1	0.7	0.8	0.7
2	0.3	0.4	0.9	0.8
3	0.8	0.1	0.6	0.5
4	0.1	0.9	1.7	0.5
5	2.5	0.6	1.5	0.7
6	0.3	0.5	1.7	0.5
7	2.5	1.0	1.2	0.6
8	1.1	0.3	1.1	0.6
9	0.1	0.2	0.7	0.5
10	1.2	0.5	0.4	0.5
11	0.0	0.6	0.7	0.4
12	0.4	0.6	0.8	0.5
Estimated parameters				
	Parameter	Standard deviation	T - statistics	P-value
a_0	3.78	0.60	6.27	0.00
a_1	-0.22	0.07	-3.10	0.02

This model is based on the equation presented in formula 1.

Table 3: Forecast characteristics - industrial production

Month of publication	Consensus - Forecasts error		Forecasters' disagreement	
	2020	Median 2015-2019	2020	Median 2015-2019
1	2.2	1.4	2.2	2.3
2	0.8	1.3	1.5	2.8
3	2.9	1.2	1.8	1.4
4	0.2	2.2	6.4	1.7
5	12.2	2.4	6.8	2.1
6	0.6	1.1	5.3	1.8
7	7.8	0.6	2.9	2.0
8	3.2	0.7	4.7	2.3
9	1.3	2.4	2.2	1.7
10	2.5	0.9	2.0	1.1
11	0.0	1.2	1.5	1.5
12	2.1	0.6	2.8	2.0
Estimated parameters				
	Parameter	Standard deviation	T - statistics	P-value
a_0	4.63	0.57	8.17	0.00
a_1	-0.31	0.07	-4.65	0.00

This model is based on the equation presented in formula 1.

Table 4: Forecast characteristics – Retail sales

Month of publication	Consensus - Forecasts error		Forecasters' disagreement	
	2020	Median 2015-2019	2020	Median 2015-2019
1	0.1	2.1	1.9	1.7
2	1.0	1.8	1.7	1.3
3	3.2	0.5	1.5	1.1
4	7.0	1.5	9.0	1.2
5	3.9	1.8	7.7	1.4
6	4.3	0.6	4.9	1.1
7	1.7	0.5	3.2	0.9
8	3.6	0.5	3.0	1.1
9	2.1	0.7	2.1	1.1
10	0.1	1.7	2.9	0.7
11	1.7	0.7	3.4	1.0
12	2.1	1.6	2.5	1.2
Estimated parameters				
	Parameter	Standard deviation	T - statistics	P-value
a_0	7.61	1.31	5.80	0.00
a_1	-0.46	0.16	-2.98	0.02

This model is based on the equation presented in formula 1.

Table 5: Revisions of unemployment rate forecasts – panel model

Horizon (quarters)	1	2	3
a_1	-0.40 (0.06, 0.00)	-0.30 (0.06, 0.00)	-0.36 (0.06, 0.00)
a_0	-0.59 (0.08, 0.00)	-0.36 (0.09, 0.00)	-0.31 (0.09, 0.00)
Periods	3	3	3
Cross sections	31	31	31
Observations	93	93	93
R-squared	0.69	0.60	0.66

This model is based on the equation presented in formula 2. Negative parameter a_0 *denotes excessive pessimism regarding labor market conditions amongst the forecasters; their estimates of the unemployment rate were systematically lowered with the next surveys.*

Table 6: Revisions of GDP forecasts – panel model

Horizon (quarters)	1	2	**3**
a_1	-0.25 (0.06, 0.00)	-0.27 (0.09, 0.00)	-0.44 (0.09, 0.00)
a_0	-1.78 (0.26, 0.00)	-1.05 (0.27, 0.00)	-1.12 (0.22, 0.00)
Periods	3	3	3
Cross sections	31	31	31
Observations	93	93	93
R-squared	0.58	0.55	0.50

This model is based on the equation presented in formula 2. Negative parameter a_0 *denotes excessive pessimism regarding economic activity amongst the forecasters; their estimates of GDP growth were expected to improve with the next surveys.*

Table 7: Revisions of Consumption forecasts – panel model

Horizon (quarters)	1	2	3
Revision - unemployment	0.33 (0.26, 0.21)	0.25 (0.19, 0.19)	0.11 (0.21, 0.61)
Constant	-0.80 (0.31, 0.01)	-0.53 (0.27, 0.06)	0.13 (0.32, 0.68)
Periods	3	3	3
Cross sections	31	31	31
Observations	93	93	93
R-squared	0.38	0.35	0.38

This model is based on the equation presented in formula 3. The positive parameter a_1 *shows that the assumption over labor market played a relatively minor role in shaping forecasts for economic activity even for the longer horizons, when employment assumptions should be more significant.*

Table 8: Revisions of Consumption forecasts (3Q ahead) – cross section estimates

Poll	April 2020	July 2022	October 2020	January 2021
Model parameters				
Revision - unemployment	-0.66 (0.31, 0.04)	-0.49 (0.34, 0.16)	0.70 (0.65, 0.29)	-1.22 (0.68, 0.08)
Constant	-1.64 (1.08, 0.14)	-0.14 (0.62, 0.82)	2.03 (0.57, 0.00)	-1.82 (0.45, 0.00)
R-squared	0.13	0.07	0.04	0.10
Actual data - average revision of the:				
Unemployment rate	3.0	-0.7	-0.5	-0.4
Consumption growth rate	-3.6	0.2	1.7	-1.3
What magnitude of revision in consumption forecast is explained by the:				
Change in the labor market assumption	-2.0	0.3	-0.3	0.5
Exogenous factors (constant)	-1.6	-0.1	2.0	-1.8
Implied random disturbance	0.0	0.1	0.0	0.0

This model is based on the equation presented in formula 3—within a single period.